Dynamic Pricing Based and Electric Vehicle Assisted Demand Response Strategy

Xing Luo*†, Xu Zhu*,Eng Gee Lim†
*Department of Electrical Engineering and Electronics, The University of Liverpool, Liverpool, UK
Email: {sgxluo2, xuzhu}@liverpool.ac.uk
†Department of Electrical and Electronic Engineering, Xi'an Jiaotong-Liverpool University, Suzhou, P. R. China
Email: enggee.lim@xjtlu.edu.cn

***Abstract*—The usage of EVs as energy storage units via vehicle-to-home (V2H) provides an effective solution to load shaping at the end-user premises since it enables householder to alleviate the load burden of power grid and save bills simultaneously. In this paper, an innovative demand response (DR) strategy with an EV auxiliary power supply (EV-APS) model is proposed, to jointly optimize the household appliance scheduling and economic cost based on dynamic pricing (DP). The proposed DR strategy takes account of the comprehensive impacts of EVs charging behaviors, user preferences, distributed generation and load priority. The effectiveness of the proposed DR strategy is verified by numerical results in terms of load balancing and cost reduction. It also significantly outperforms the previous DR approaches.**

I. INTRODUCTION

Electric vehicles (EVs) have become increasingly popular in recent years due to their environmental and economic benefits, and the rapid advance of rechargeable battery technology [1]–[3]. Meanwhile, an increasing adoption of EVs brings about both opportunities and challenges for smart grid along with worldwide application of dynamic pricing (DP) [4]. As the EVs are in fact involved in the power grid by plugging in at consumer premises, the charging power of EV leads to an increase in electric demand. However, the usage of EVs as energy storage units via vehicle-to-home (V2H) provides an effective solution to load shaping at demand side. In addition, householders are able to participate in load shifting and may have multiple options in energy allocation.

As an effective method for reducing energy wastage, demand response (DR) management for residents plays a significant role in both balancing energy supply and demand, and enhancing the reliability in smart grid [5]. The basic principle of DR management is to shift the operating time of home appliances automatically or manually during high-price periods and gain the benefits from low-price periods, thus achieving the aim of saving electric bills for customers [6]. In other ways, it is also benefit to power grid as it offers an effective solution to average the power usage at different time so that alleviates the load burden of power grid, especially in peak demand time. Therefore, the research on DR strategy is quite meaningful and worthy for both householders and power suppliers. Considering the flexible energy storage purpose of EVs, the realisation of a DR management strategy coordinated with EVs becomes possible.

The implementation of DR with EVs requires efficient energy distribution management and high-performance batteries as basis. Moreover, DP provides a basic control signal to optimally schedule the charging and discharging behaviors of EVs, by minimizing the overall cost [7]. Compared with the conventional energy storage system (ESS) and other energy production facilities, using EVs as an auxiliary power source has advantages in employing flexibility and economical efficiency. It does not expect extra investment besides the daily used EVs. Therefore, the DR strategy with EVs holds wide prospects in practice.

Much research has been conducted on demand response and there are many popular DR strategies being presented in literatures. In [8], a user-expected price (UEP) based DR strategy was proposed as an indicator of differential pricing in dynamic domestic electricity tariffs, and exploited the modern smart grid infrastructure to respond to these dynamic pricing structures. However, the impact of including an EV which can also be beneficial for load clipping in certain periods has not been considered.

In [9], an optimization framework based DR program was proposed, with high penetration of EVs and storage systems from residential customers perspective as well as utility companys perspective. The simulation results showed that the appropriate scheduling has benefits for both customers and suppliers. However, the charging profiles of EVs that may significantly affect the performance of the model have not been accounted in [9].

Furthermore, Develder et al. [10] focused on EVs' charging behaviors by using collected data from EV charging sessions. Three different types of charging behavior were derived and the potential of EVs charging behaviors for DR exploitation was analyzed. Nevertheless, the specific DR strategy with considering EVs' types of charging behavior has not been proposed.

In addition to the above, numerous approaches have been proposed to address the DR optimization problems. For example, a DR strategy was proposed in the context of a smart distribution network in [3]. In [11], a DR strategy for residential customers as opposed to commercial ones was introduced. In [12], the authors proposed an algorithm for distributed DR of the EVs to shape the daily demand profile. Additionally, a new model of demand response management for the future smart grid that integrates plug-in electric vehicles and renewable distributed generators was described in [13]. In [14], a method for the residential load scheduling was presented based on human behaviors analysis.

In this paper, we propose a DP based and EV assisted DR strategy, for household appliance scheduling, in order to alleviate the load burden for the grid and save bills for householders simultaneously. Our work is different in that we utilize EV as an auxiliary power supply (APS) for household appliances and that we consider various affecting factors such as user preferences, EV's charging behavior and load priority for scheduling. The effectiveness of the proposed EV-APS based DR strategy is verified by numerical results, which demonstrate that 86.4% of the load can be shaped to a low level in peak demand hours and that the daily electric cost can be reduced by 30.6%. The EV-APS based DR strategy also significantly outperforms the DR approach in [15].

The rest of this paper is organized as follows. Section II presents the EV-APS demand response network overall. In Section III, two significant power supply models are thoroughly discussed. Additionally, the problem formulation and optimization are presented in Section IV. In Section V, a case study is carried out to evaluate the feasibility of the proposed strategy. Finally, we conclude the paper in Section VI.

II. EV-APS Demand Response Network

This section illustrates an overall description of the proposed EV-APS demand response network.

The schematic diagram of the proposed DR strategy with EV-APS model is showed in Fig. 1. Specifically, householders buy electricity from the power grid for the daily usage including EV charging under the dynamic pricing tariff. Normally, the domestic appliances are directly powered by the main power grid. However, as an interim energy storage unit, EV is able to supply power for the household appliances in auxiliaries on appropriate occasions, especially in high price periods. The time of activating EV-APS is dependent on the instructions from the smart controller.

In addition, the smart controller plays the role as a supervisor in the system network. It regulates the energy sources supplying and the operating time of the household appliances based on real-time load information which is received from the smart meter, and other signals (e.g. DP, EV status, load priority and etc.).

In general, more than 20 types of household appliances will be used in domestic homes. Considering the operating characteristic of each appliance, it is not necessary to schedule all of them via the proposed network. Hence, in accordance with the device operating characteristics, the household appliances can be classified into different scenarios. As a result, the appliances are sorted into two main scenarios in this study.

- Critical Scenario (CS). CS contains the appliances that have to be used at a specified time or cannot be scheduled. Examples include lightings, TV, laptop and etc.;

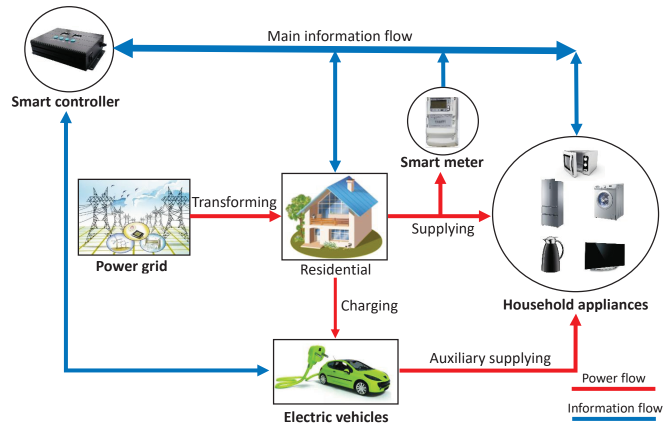


Fig. 1. Schematic diagram of a fundamental DR strategy with EV-APS model for domestic homes

- Flexible Scenario (FS). FS contains the appliances that can be powered on with a tolerable delay and have a flexible operating time. Hot water tank and washer are typical representatives in FS.

Moreover, both CS and FS will be accounted in the proposed EV-APS DR strategy. The initial idea of DR management at the end-user premises is to save electric bill through shifting the operating time of the household appliances during high price time periods and alleviate the load burden simultaneously. Considering the EVs as an auxiliary power source for household appliances, multiple choices are provided to DR management and energy allocation. The detailed power supply models will be discussed in next section.

III. Power Supply Models

In this section, the formulation of the EV-APS DR strategy consisting of the main power supply model and EV auxiliary power supply model is thoroughly analyzed.

A. Main Power Supply Model

We define variable W_{grid} as the total energy consumption and variable P^t_{grid} as the total load power on grid at time t. Afterwards, the main power supply model including the corresponded constrains can be presented as:

$$W_{\text{grid}} = \int_{T_{\text{in}}}^{T_{\text{term}}} P^t_{\text{grid}} \cdot d(t) \tag{1}$$

$$P^t_{\text{grid}} = P^t_{\text{AP}} + P^t_{\text{EV,ch}} - P^t_{\text{EV,dis}} \tag{2}$$

$$P^t_{\text{AP}} = \sum_{j=1}^{n} P^t_{\text{CS},j} + \sum_{i=1}^{m} P^t_{\text{FS},i} \cdot \varepsilon_i \tag{3}$$

Subject to:

$$\forall t \in [T_{\text{in}}, T_{\text{term}}], \; P^t_{\text{grid}} \leqslant P^{\max}_{\text{grid}} \tag{4}$$

$$P^t_{\text{EV,ch}} = 0, \text{ if } P^t_{\text{EV,dis}} > 0, \tag{5}$$

$$P^t_{\text{EV,dis}} = 0, \text{ if } P^t_{\text{EV,ch}} > 0, \tag{6}$$

Equation (1) indicates that the total energy consumption (W_{grid}) is equal to the integral of total power (P^t_{grid}) through the time that is between initial time T_{in} and terminate time T_{term}. Equation (2) illustrates the relationships between the total power and each power consumed component. P^t_{AP} is the load power consumed by the household appliances at time t. $P^t_{\text{EV,ch}}$ and $P^t_{\text{EV,dis}}$ represent the power rates of the EV charging and discharging, respectively.

Additionally, as it is showed in Equation (3), P^t_{AP} consists of the power cost by CS appliances ($P^t_{\text{CS},j}$) and FS ($P^t_{\text{FS},i}$) appliances, where j and i are the index of the appliances. The ε parameters have small positive values (e.g. 1+e^{-8}, 1+2e^{-8} and 1+3e^{-8}) that are determined by assumptions. Thus, the total power of appliances is not affected. This setting meets the requirement of having a priority according to user preferences in scheduling the FS appliances. The smaller value of ε indicates a higher priority in scheduling process by the DR management system.

In spite of that, $P^{\max}_{\text{grid}}$ is proposed in constraint (4) to limit the maximum power rate on grid at time t for safety and power distribution considerations. Further, constraints (5) and (6) express that the battery charging and discharging cannot execute simultaneously otherwise the battery will be damaged to a certain extent.

B. EV Auxiliary Power Supply Model

Determining the EV-APS model requires sufficient knowledge from previous researches. According to the investigation of the current EV market, Table I illustrates the core parameters of five major-brands of EVs around the world [16]–[18]. The parameters include the battery capacity BC, the discharging power $P_{\text{EV,dis}}$ and the driving range per charge RC.

Moreover, multiple charging schemas are provided for each EV. In Section V, the Tesla-Model-S is taken as an example in this study and Table II shows the relevant charging schemes that will be considered in the DR strategy. It can be seen that the charging power $P_{\text{EV,ch}}$ plays as an important role in the grid due to the high power rate of battery charging.

Further, variables $W^1_{\text{EV,in}}$ and $W^2_{\text{EV,in}}$ are defined as the initial energy storage when people leave home in the morning of the 1st day and the 2nd day, respectively. Therefore, the EV model can be proposed as below.

$$W^1_{\text{EV,in}} = W_{\text{EV,remain}} + W_{\text{EV,road}} \tag{7}$$

$$W_{\text{EV,road}} = \frac{BC}{RC} \cdot \text{Distance} \tag{8}$$

$$W^2_{\text{EV,in}} = W_{\text{EV,remain}} + W_{\text{EV,ch}} - W_{\text{EV,dis}} \tag{9}$$

$$W_{\text{EV,ch}} = \int_{T_{c,b}}^{T_{c,e}} \eta_1 \cdot P^t_{\text{EV,ch}} \cdot d(t) \tag{10}$$

$$W_{\text{EV,dis}} = \int_{T_{d,b}}^{T_{d,e}} \eta_2 \cdot P^t_{\text{EV,dis}} \cdot d(t) \tag{11}$$

Subject to:

$$\forall t,\ BC^{\min} \leqslant W^t_{\text{EV}} \leqslant BC^{\max} \tag{12}$$

$$\forall t \in [T_{d,b}, T_{d,e}],\ P^t_{\text{EV,dis}} \leqslant P^{\text{rated}}_{\text{EV,dis}} \tag{13}$$

$$\emptyset = [T_{c,b}, T_{c,e}] \cap [T_{d,b}, T_{d,e}] \tag{14}$$

Equation (7) - (8) indicate the state relations between the 1st day initial energy ($W^1_{\text{EV,in}}$), the remaining energy ($W_{\text{EV,remain}}$) and the energy consumption on road ($W_{\text{EV,road}}$). It is apparent that $W_{\text{EV,road}}$ is directly proportional to the driving distance. Additionally, Equation (9) enforces that the remaining energy of EV can be used to cover a portion of energy usage by household appliances via battery discharging ($W_{\text{EV,dis}}$). The EV will be charged to an appropriate level for the usage of the 2nd day.

Moreover, Equation (10) explains the relationship between the total energy charging ($W_{\text{EV,ch}}$) and the charging power rate ($P^t_{\text{EV,ch}}$). η_1 is the battery charging efficiency. Time parameters $T_{c,b}$ and $T_{c,e}$ denote the begin time and the end time of the charging operation. Meanwhile, the battery discharging occasion is described in Equation (11) which is similar to Equation (10).

Despite that, constraint (12) presents a limit on the the actual amount energy of the EV battery. It can not drop below the minimum allowed battery capacity ($BC^{\min}$) or exceed the maximum allowed battery capacity ($BC^{\max}$). Constraint (13) limits the actual discharging power rate ($P^t_{\text{EV,dis}}$) to be less than the rated power of the EV. Additionally, since battery damages will be caused by the simultaneous charging and discharging, constraint (14) restricts the operation time of battery charging and discharging.

IV. Problem Formulation and Optimization

According to the previous analysis, the problem in this study can be formulated as minimizing the total cost (TC) by scheduling the operating time of the household appliances. Hence, the objective function can be proposed as:

$$\text{Minimize } TC = \int_{T_{\text{in}}}^{T_{\text{term}}} W_{\text{grid}} \cdot P_{\text{tariff}} \cdot d(t) \tag{15}$$

where the variable W_{grid} represents the total energy bought from the power grid in time period $[T_{\text{in}}, T_{\text{term}}]$. Additionally, the price variable P_{tariff} is time dependent and varies hourly depending on the total load demand [19]. The DP tariff that is used in simulation is given in Fig. 2 in Section V.

In order to obtain the optimal solution and reduce the cost to the minimum, the exhaustive search technique can be used on the basis of the established models. The description of the technique is not the focus of this work and is not emphasized here.

Under the given constraints, the programme is continuously searching the solutions of appliances allocation by minimizing the global cost according to the DP signals. The objective appliances in FS are scheduled in sequence based on the pre-set priority. Meanwhile, as the auxiliary power source, the

TABLE I
THE MAJOR-BRANDS OF EVS IN CURRENT MARKET

Manufacturer and Model	Battery Capacity	Discharging Power	Driving Range per Charge
Tesla, Model-S (EV)	60 kWh	3.0 kW	273 miles
BYD, Tang-100 (HEV)	23 kWh	3.3 kW	63 miles
BMW, i3 (EV/HEV)	33 kWh	2.5 kW	114 miles
GM, Chevrolet Bolt (EV)	60 kWh	-	283 miles
Nissan, Leaf (EV)	30 kWh	-	107 miles

TABLE II
TESLA-MODEL-S CHARGING SCHEMES

Charging Circuit	Charging Power	Charging Speed	Time Cost per 100 miles
Wall connector (1-phase grid)	7.4 kW	22 miles/hr	4.5 hr
Wall connector (3-phase grid)	11 kW	34 miles/hr	2.9 hr
High power charger upgrade	16.5 kW	51 miles/hr	2.0 hr
3-pin domestic adapter	2.3 kW	6.8 miles/hr	14.7 hr

operating time of EV discharging is dependent on the EV status and the load demand. In this study, the remaining EV energy is assumed to be firstly consumed in high price hours to ensure the maximum utilization of storage.

To evaluate the feasibility of the EV-APS DR strategy, a case study is proposed in next section.

V. NUMERICAL RESULTS

This section demonstrates how the proposed EV-APS DR strategy can be implemented at the household level to alleviate the load burden in peak demand periods and save electric bills. Some assumptions for simulations are presented.

A. Case Study Description

First of all, the selected time interval for the optimization is set as 3 minutes (0.05 hr). The households comprise over 15 types of common used loads covering both CS and FS. The rated power and the pre-set operating time of the corresponded appliances are given in Table III. The EV and four other common used appliances, hot water tank, dish machine, washer and drying machine, are considered as the flexible loads in this study.

In addition, the ε parameters are given to indicate the priorities of the related loads. According to the user preferences, it is assumed as, $\varepsilon_0 < \varepsilon_1 < \varepsilon_2 < \varepsilon_3 < \varepsilon_4$, which means the operating of EV charging obtains the highest priority in scheduling among all FS loads. Besides, in accordance with the operating habits, the objective scheduling time for these appliances are set as: EV charging, [0:00-8:00]; hot water tank, [17:00-22:00]; dish machine, [18:30-24:00]; washer, [17:00-24:00]; drying machine, [0:00-8:00].

Moreover, the Tesla-Model-S (EV) with a battery rating of 30 kWh (up to 60 kWh) is employed in the case study. On the one hand, it is provided with a charging wall connector (1-phase grid) limited to a charging power of 7.4 kW. On the other hand, the discharging power for household appliances is up to 3.0 kW as it is showed in Table I. The charging and discharging efficiencies are considered as η_1=η_2=0.95. It is also considered that the householder always arrives home at 5:00 p.m. with 18 kWh (60%) remaining energy in EV battery and leaves home at 8:00 a.m. in the next morning with fully charged battery (100±5%, 30±1.5 kWh). However, the minimum remaining energy in EV is restricted to 7.5 kWh (25±5%) to avoid the deep discharging. The deep charging will cause damages to the battery and reduce battery life [20].

TABLE III
PRE-SET HOUSEHOLD APPLIANCES INFORMATION

CS Appliances	Power (kW)	Operating Time
Refrigerator	0.1	0:00-24:00
Water Dispenser	0.1	0:00-24:00
Toaster	0.6	7:30-7:45
Microwave Oven1	2.4	7:30-8:00
Lights	0.4	17:00-24:00
Electric Cooker	0.5	17:00-17:45
Electric Kettle	2.0	17:15-17:30
Microwave Oven2	2.4	17:30-18:00
Television	0.2	18:00-23:00
Cleaner	0.9	19:00-19:30
Laptop	0.4	21:00-23:30
Hair-Drier	2.0	22:30-23:00
FS Appliances	**Power (kW)**	**Operating Time**
EV, ε_0	7.4	18:00-20:00
Hot Water Tank, ε_1	2.5	20:00-22:00
Dish Machine, ε_2	0.5	18:30-19:15
Washer, ε_3	0.6	19:00-20:15
Drying Machine, ε_4	2.5	20:30-21:30

Furthermore, the UK dynamic pricing data of a typical day [21] which is used in this case is presented in Fig. 2.

B. Simulation Results

Assuming that the target household demand limits of 8 kW all day in this study, Fig. 3 presents the overall load shaping results of the household appliances. Specifically, Fig. 3 (a) shows the original load profile without DR. It can be seen that the peak demand time occurs between 6:00 p.m. and 8:10 p.m. The total house load exceeds the 8 kW limit during this period and the maximum load demand is 11.5 kW which occurs at around 8:00 p.m. Additionally, (b) and (c)

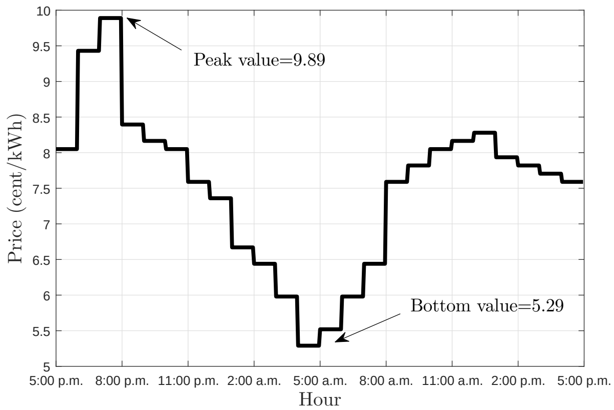


Fig. 2. UK real-time pricing data

present the load profiles after scheduling by using a LSC DR strategy [15] and the proposed EV-APS DR strategy, respectively. Apparently, the load burden is alleviated and the load decreases to an appropriate level in both (b) and (c). Nonetheless, compared with the results in (b), the load demand in (c) between 6:00 p.m. and 9:40 p.m. approaches to a very low level, since the EV discharging is activated during this time. As a consequence, the EV takes 3.2 hours to charge as it is showed in (c), which is longer than the charging time (2.1 hours) in (b).

Moreover, since the EV plays a great role in power supplying in modeling, the real-time EV remaining energy variation at household parking station by using the proposed EV-APS DR strategy is illustrated in Fig. 4.

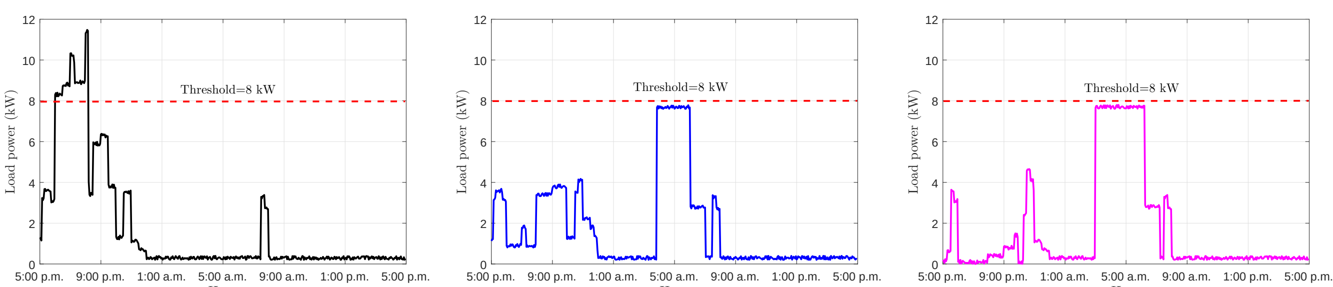
Specifically, the EV arrives at home at 5:00 p.m. as it describes in the figure. Between 5:00 p.m. and 10:18 p.m., the EV discharging is activated and a part of household appliances are continuously powered by EV until the amount of EV remaining energy reaches the minimum threshold (7.5 kWh). However, the EV is charged from 3:00 a.m. to 6:18 a.m. in the next day morning to enable the EV leaves with the fully charged battery at 8:00 a.m. According to the results, it can be seen that the EV remaining energy variation directly corresponds with the load curve in Fig. 3 (c), which indicates that this emulation method is correct and feasible.

Furthermore, Fig. 5 shows the accumulative probabilities of the reshaped load distributions by DR strategies during peak load demand period which is between 5:00 p.m. and 12:00 p.m. Based on the figure, we can see that the probabilities for the case $P_{\text{grid}} < 1$ kW of the original load profile without DR, the LSC DR shaping profile and the EV-APS DR shaping profile are 7.1%, 24.3% and 72.9%, respectively. For the case $P_{\text{grid}} < 3$ kW, the probabilities are 23.6%, 53.1% and 86.4%, respectively. The results indicate that the load shaping performance by the EV-APS DR strategy is the best as a higher percentage load is shaped to a low level, which proves that the proposed method is an effective tool in load shaping.

The total cost is another issue that customers concern. On the basis of the DP tariff, the daily electric cost can be obtained. Fig. 6 presents the accumulative cost comparison between different demand response strategies. Obviously, the proposed EV-APS DR strategy performs superior than other approaches in comparison. The total electric bill of the original load demand in a typical day is about £3.6. However, it decreases to £2.9 and £2.5 by using the LSC DR and the EV-APS DR, respectively. The total saving cost are about £0.7 and £1.1, which are equivalent to 19.4% and 30.6%, respectively. Compared with the LSC DR strategy in literature, the proposed DR strategy in this paper has a better performance in load shaping and higher cost saving percentage (11.2% improved), obviously.

VI. CONCLUSION

The aim of this work is to develop a demand response strategy with EVs, to jointly optimise the household appliance scheduling and economic cost based on DP. The effectiveness of the proposed EV-APS based DR strategy is verified by numerical results, which demonstrate that 86.4% of the load can be shaped to a low level in peak demand hours and that the daily electric cost can be reduced by 30.6%. According to the results, we can conclude that the proposed demand response strategy is an energy-efficient tool and can fulfill the tasks of load shaping and saving bills.



(a) (b) (c)

Fig. 3. The overall load shaping results. The load profiles of (a) without DR; (b) by the LSC DR; (c) by the proposed EV-APS DR

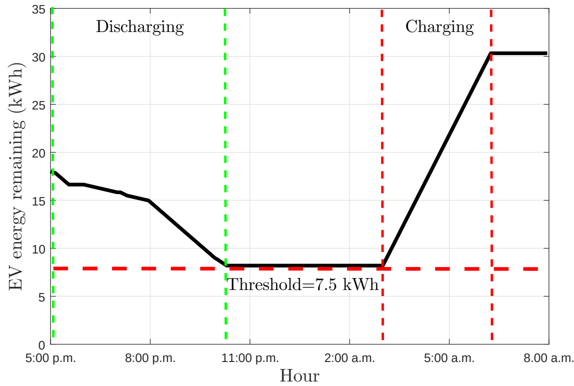


Fig. 4. The real-time EV remaining energy variation at parking station

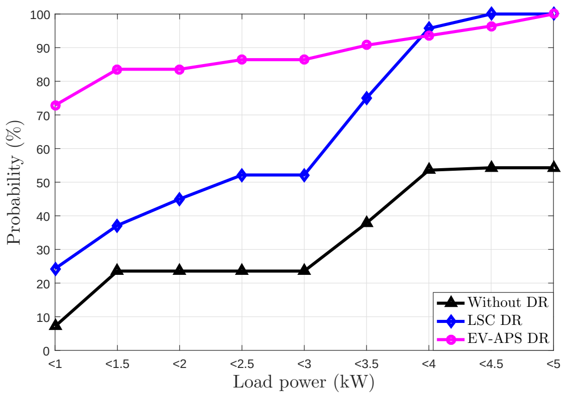


Fig. 5. The accumulative probability of the load distribution during peak load demand hours

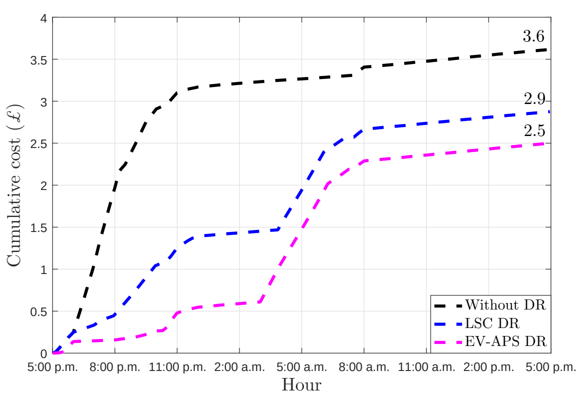


Fig. 6. The accumulative cost comparison between DR strategies

References

[1] M. Ansari, A. T. Al-Awami, E. Sortomme, and M. A. Abido, "Coordinated bidding of ancillary services for vehicle-to-grid using fuzzy optimization," *IEEE Transactions on Smart Grid*, vol. 6, no. 1, pp. 261–270, Jan. 2015.

[2] M. Yilmaz and P. T. Krein, "Review of the impact of vehicle-to-grid technologies on distribution systems and utility interfaces," *IEEE Transactions on Power Electronics*, vol. 28, no. 12, pp. 5673–5689, Dec. 2013.

[3] S. Shao, M. Pipattanasomporn, and S. Rahman, "Grid integration of electric vehicles and demand response with customer choice," *IEEE Transactions on Smart Grid*, vol. 3, no. 1, pp. 543–550, Mar. 2012.

[4] K. Qian, C. Zhou, M. Allan, and Y. Yuan, "Modeling of load demand due to ev battery charging in distribution systems," *IEEE Transactions on Power Systems*, vol. 26, no. 2, pp. 802–810, May 2011.

[5] A. Brooks, E. Lu, D. Reicher, C. Spirakis, and B. Weihl, "Demand dispatch," *IEEE Power and Energy Magazine*, vol. 8, no. 3, pp. 20–29, May 2010.

[6] C. O'Dwyer, R. Duignan, and M. O'Malley, "Modeling demand response in the residential sector for the provision of reserves," in *2012 IEEE Power and Energy Society General Meeting*, Jul. 2012, pp. 1–8.

[7] C. Wu, H. Mohsenian-Rad, and J. Huang, "Vehicle-to-aggregator interaction game," *IEEE Transactions on Smart Grid*, vol. 3, no. 1, pp. 434–442, Mar. 2012.

[8] X. Li, Hong, and S. Ho, "User-expected price-based demand response algorithm for a home-to-grid system," *Energy*, vol. 64, no. C, pp. 437–449, Jan. 2014.

[9] J. Zhao, S. Kucuksari, E. Mazhari, and Y.-J. Son, "Integrated analysis of high-penetration pv and phev with energy storage and demand response," *Applied Energy*, vol. 112, pp. 35–51, Dec. 2013.

[10] C. Develder, N. Sadeghianpourhamami, M. Strobbe, and N. Refa, "Quantifying flexibility in ev charging as dr potential: Analysis of two real-world data sets," in *2016 IEEE International Conference on Smart Grid Communications (SmartGridComm)*, Sydney, Australia, Nov. 2016, pp. 600–605.

[11] M. Pipattanasomporn, M. Kuzlu, and S. Rahman, "An algorithm for intelligent home energy management and demand response analysis," *IEEE Transactions on Smart Grid*, vol. 3, no. 4, pp. 2166–2173, Dec. 2012.

[12] F. Rassaei, W. S. Soh, and K. C. Chua, "Demand response for residential electric vehicles with random usage patterns in smart grids," *IEEE Transactions on Sustainable Energy*, vol. 6, no. 4, pp. 1367–1376, Oct. 2015.

[13] Z. Tan, P. Yang, and A. Nehorai, "An optimal and distributed demand response strategy with electric vehicles in the smart grid," *IEEE Transactions on Smart Grid*, vol. 5, no. 2, pp. 861–869, Mar. 2014.

[14] S. Chen, F. Gao, X. Guan, T. Liu, Y. Che, and Y. Liu, "A residential load scheduling approach based on load behavior analysis," in *Proc. 2014 IEEE International Conference on Automation Science and Engineering (CASE)*, New Taipei, Taiwan, Aug. 2014, pp. 954–959.

[15] X. Luo, X. Zhu, and E. G. Lim, "Load scheduling based on an advanced real-time price forecasting model," in *Proc. 2015 IEEE International Conference on Ubiquitous Computing and Communications*, Liverpool, UK, Oct. 2015, pp. 1252–1257.

[16] S. Shao, M. Pipattanasomporn, and S. Rahman, "Demand response as a load shaping tool in an intelligent grid with electric vehicles," *IEEE Transactions on Smart Grid*, vol. 2, no. 4, pp. 624–631, Dec. 2011.

[17] "[online] available: https://www.tesla.com."

[18] "[online] available: http://www.bydauto.com.cn."

[19] K. L. Lo and Y. K. Wu, "Analysis of relationships between hourly electricity price and load in deregulated real-time power markets," *IEE Proceedings - Generation, Transmission and Distribution*, vol. 151, no. 4, pp. 441–452, Jul. 2004.

[20] T. Blank, J. Badeda, J. Kowal, and D. U. Sauer, "Deep discharge behavior of lead-acid batteries and modeling of stationary battery energy storage systems," in *Intelec 2012*, Sep. 2012, pp. 1–4.

[21] "[online] available: http://www.britishgas.co.uk."